

Black Box Variational Inference with a Deterministic Objective

Faster, More Accurate, and Even More Black Box

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Problem statement

We all want to do accurate Bayesian inference quickly:

- In terms of compute (wall time, model evaluations, parallelism)
- In terms of analyst effort (tuning, algorithmic complexity)

Markov Chain Monte Carlo (MCMC) can be straightforward and accurate but slow.

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Black Box Variational Inference (BBVI) can be faster alternative to MCMC. **But...**

- BBVI is cast as an optimization problem with an intractable objective \Rightarrow
- Most BBVI methods use **stochastic gradient (SG)** optimization \Rightarrow
 - SG algorithms can be hard to tune
 - Assessing convergence and stochastic error can be difficult
- Many BBVI methods employ a **mean-field (MF) approximation** \Rightarrow
 - Posterior variances are poorly estimated

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Our proposal: replace the intractable BBVI objective with a fixed approximation.

- Better optimization methods can be used (e.g. true second-order methods)
- Convergence and approximation error can be assessed directly
- Can correct posterior covariances with linear response covariances
- This technique is well-studied (but there's still work to do in the context of BBVI)

\Rightarrow **Simpler, faster, and better BBVI posterior approximations ... in some cases.**

- BBVI Background and our proposal
 - Automatic differentiation variational inference (ADVI) (a BBVI method)
 - Our approximation: “Deterministic ADVI” (DADVI)
 - *Linear response (LR) covariances
 - *Estimating approximation error

* Not covered in today's talk — see our paper!

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- Experimental results: DADVI vs ADVI
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 - DADVI’s posterior mean estimates’ accuracy are comparable to ADVI
 - *DADVI+LR provides more accurate posterior variance estimates than ADVI
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 - *DADVI provides accurate estimates of its own approximation error
- Sketch of theory and work to be done!

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Notation

Data: y

Likelihood: $\mathcal{P}(y|\theta)$

Parameter: $\theta \in \mathbb{R}^{D_\theta}$

Prior: $\mathcal{P}(\theta)$ (density w.r.t. Lebesgue \mathbb{R}^{D_θ} , nonzero everywhere)

We will be interested in means and covariances of the posterior $\mathcal{P}(\theta|y)$.

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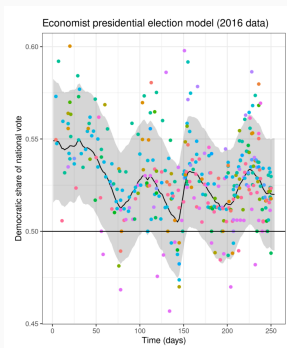
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Example: Election modeling (2016 US POTUS)

Data y : Polling data (colored dots)

Likelihood $\mathcal{P}(y|\theta)$: Time series with random effects

Parameter θ : 15,098-dimensional

Interested in: Vote share on election day

MCMC time: 643 minutes (PyMC NUTS)

How can we approximate the posterior more quickly?

One answer: variational inference.

We want the posterior $\mathcal{P}(\theta|y)$. Let $\text{KL}(\mathcal{Q}(\theta)||\mathcal{P}(\theta))$ denote KL divergence:

$$\text{KL}(\mathcal{Q}(\theta)||\mathcal{P}(\theta)) = \mathbb{E}_{\mathcal{Q}(\theta)} [\log \mathcal{Q}(\theta)] - \mathbb{E}_{\mathcal{Q}(\theta)} [\log \mathcal{P}(\theta)] .$$

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Variational inference: $\hat{\mathcal{Q}}^*(\theta) = \underset{\mathcal{Q} \in \Omega_{\mathcal{Q}}}{\text{argmin}} \text{KL}(\mathcal{Q}(\theta)||\mathcal{P}(\theta|y)) \quad \dots \text{ for restricted } \Omega_{\mathcal{Q}}$

How can we optimize this objective?

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How can we optimize this objective? **Black-box VI [Ranganath et al., 2014]:**

- Parameterize the family $\Omega_{\mathcal{Q}}$ using $\eta \in \mathbb{R}^{D_{\eta}}$ (so we have $\mathcal{Q}(\theta|\eta)$)
 - We will study **ADVI**, which takes $\mathcal{Q}(\theta|\eta)$ to be Gaussian [Kucukelbir et al., 2017].
 - The parameters η are the means and covariance (“mean-field” or “full-rank”)
- Re-write the objective (using the reparameterization trick) as

$$\underset{\eta}{\text{argmin}} F(\eta) \quad \text{where} \quad F(\eta) := \mathbb{E}_{\mathcal{N}_{\text{std}}(z)} [f(\eta, z)].$$

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 - “Stochastic gradient” (used by almost all the BBVI community)
- Minimize a stochastic approximations to $F(\eta)$ (with exact gradients thereof)
 - The “sample average approximation” (**our proposal**)

Two approaches

Consider $\hat{Q}^*(\theta) = \underset{\eta}{\operatorname{argmin}} F(\eta)$ where $F(\eta) := \mathbb{E}_{\mathcal{N}_{\text{std}}(z)} [f(\eta, z)]$.

Let $\mathcal{Z}_N = \{z_1, \dots, z_N\} \stackrel{iid}{\sim} \mathcal{N}_{\text{std}}(z)$, and let $\hat{F}(\eta|\mathcal{Z}_N) := \frac{1}{N} \sum_{n=1}^N f(\eta, z_n)$.

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Algorithm 1

Stochastic gradient (SG)

ADVI (and most BBVI)

Fix N (typically $N = 1$)

$t \leftarrow 0$

while Not converged **do**

$t \leftarrow t + 1$

 Draw \mathcal{Z}_N

$\Delta_S \leftarrow \nabla_{\eta} \hat{F}(\eta_{t-1}|\mathcal{Z}_N)$

$\alpha_t \leftarrow \text{SetStepSize}(\text{Past state})$

$\eta_t \leftarrow \eta_{t-1} - \alpha_t \Delta_S$

 AssessConvergence(Past state)

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return η_t or $\frac{1}{M} \sum_{t'=t-M}^t \eta_{t'}$

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Algorithm 2

Sample average approximation (SAA)

Deterministic ADVI (DADVI) (**proposal**)

Fix N (our experiments use $N = 30$)

Draw \mathcal{Z}_N

$t \leftarrow 0$

while Not converged **do**

$t \leftarrow t + 1$

$\Delta_D \leftarrow \text{GetStep}(\hat{F}(\cdot|\mathcal{Z}_N), \eta_{t-1})$

$\eta_t \leftarrow \eta_{t-1} + \Delta_D$

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Our proposal: Apply Algorithm 2 with the ADVI objective.

Take **better steps**, easily **assess convergence**, with less tuning.

For each of a range of models (next slide), we compared:

- **NUTS:** The “no-U-turn” MCMC sampler as implemented by PyMC [Salvatier et al., 2016]. We used this as the “ground truth” posterior.

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Stochastic ADVI methods:

- Mean field ADVI: We used the PyMC implementation of ADVI, together with its default termination criterion (based on parameter differences).
- Full-rank ADVI: We used the PyMC implementation of full-rank ADVI, together with the default termination criterion for ADVI described above.
- RAABBVI: To run RAABBVI, we used the public package `viabel`, provided by Welandawe et al. [2022].

We terminated unconverged stochastic ADVI after 100,000 iterations.

We evaluated each method on a range of models.

Model Name	Dim D_θ	NUTS runtime	Description
ARM (53 models)	Median 5 (max 176)	median 39 seconds (max 16 minutes)	A range of linear models, GLMs, and GLMMs
Microcredit	124	597 minutes	Hierarchical model with heavy tails and zero inflation
Occupancy	1,884	251 minutes	Binary regression with highly crossed random effects
Tennis	5,014	57 minutes	Binary regression with highly crossed random effects
POTUS	15,098	643 minutes	Autoregressive time series with random effects

Table 1: Model summaries.

Posterior mean accuracy

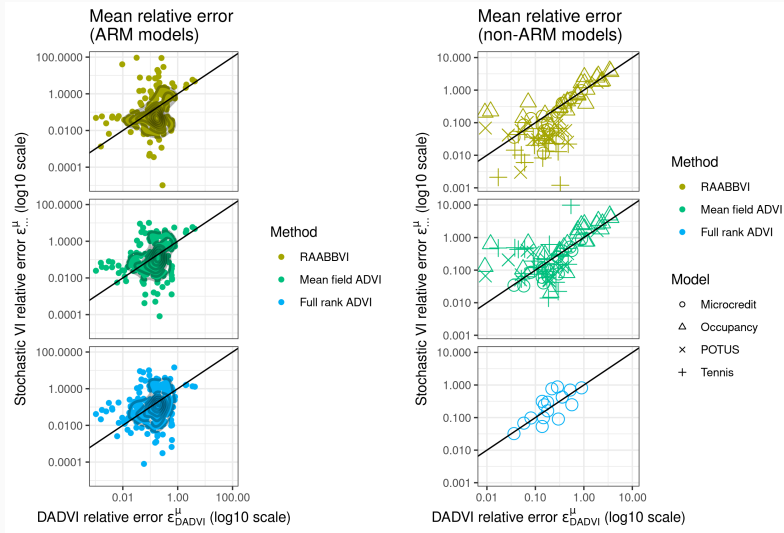


Figure 1: Posterior mean accuracy (relative to MCMC posterior standard deviation). Each point is a single named parameter in a single model. Points above the diagonal line indicate better DADVI or LRVB performance.

Computational cost for ARM models

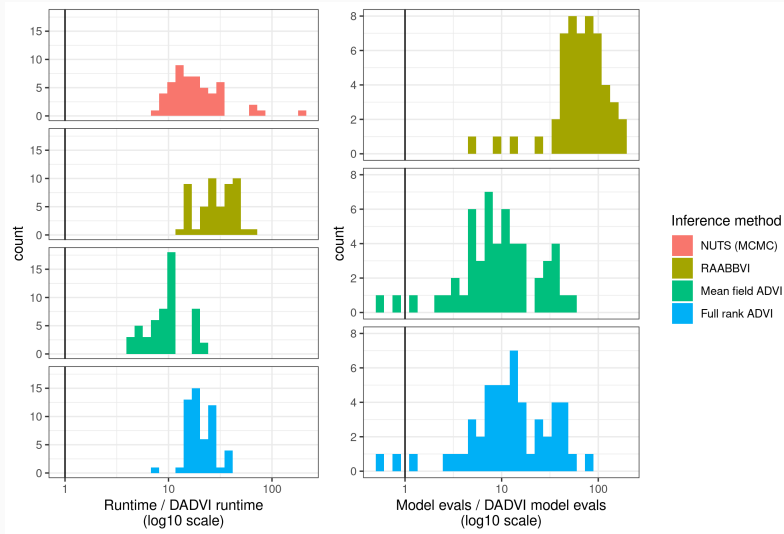


Figure 2: Runtimes and model evaluation counts for the ARM models. Results are reported divided by the corresponding value for DADVI.

Computational cost for non-ARM models

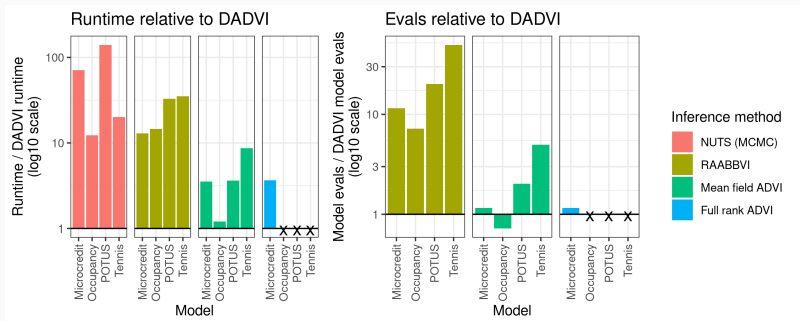


Figure 3: Runtimes and model evaluation counts for the non-ARM models. Results are reported divided by the corresponding value for DADVI. Missing model / method combinations are marked with an X.

Optimization traces for ARM models

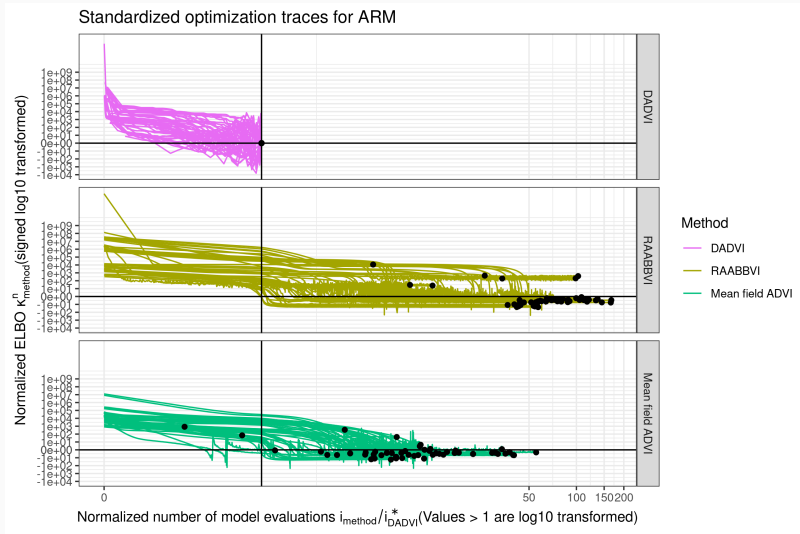


Figure 4: Optimization traces for the ARM models. Black dots show the termination point of each method. Dots above the horizontal black line mean that DADVI found a better ELBO. Dots to the right of the black line mean that DADVI terminated sooner in terms of model evaluations.

Optimization traces for non-ARM models

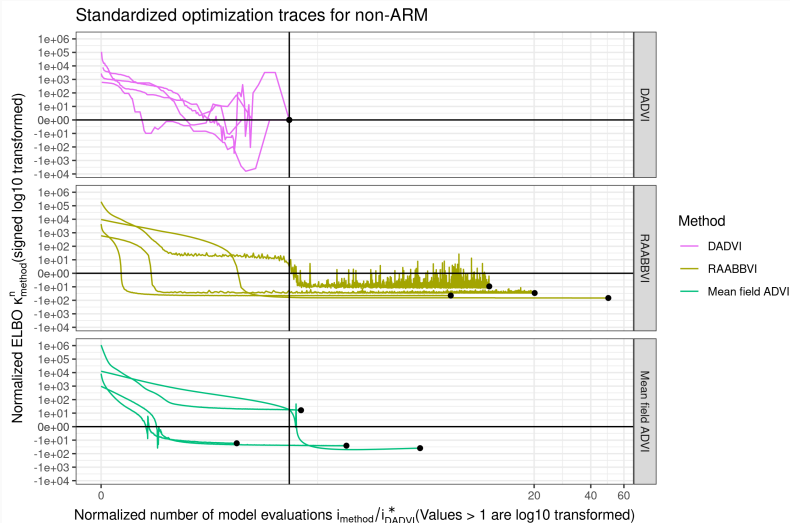


Figure 5: Traces for non-ARM models. Black dots show the termination point of each method. Dots above the horizontal black line mean that DADVI found a better ELBO. Dots to the right of the black line mean that DADVI terminated sooner in terms of model evaluations.

⇒ DADVI is faster, simpler, and the posterior means are not worse.

But DADVI can additionally provide:

- Simple estimates of approximation error
- Improved (LR) posterior covariance estimates

See paper for details!

Posterior standard deviation accuracy

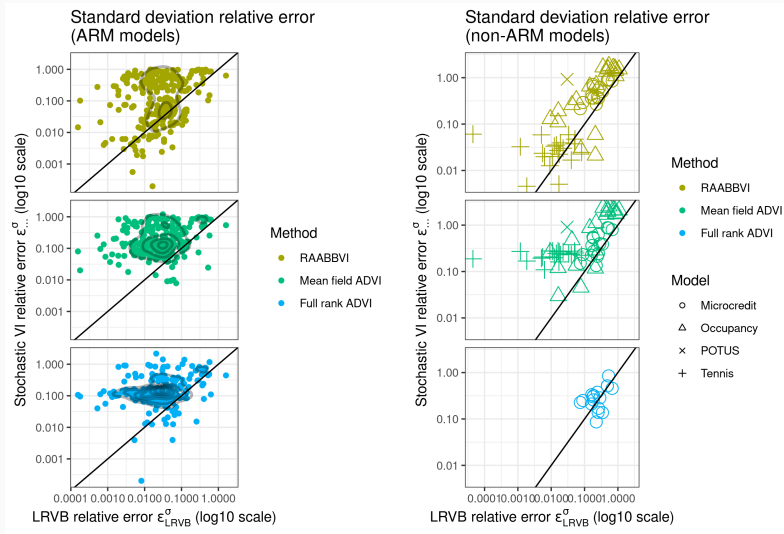


Figure 6: Posterior sd relative accuracy. Each point is a single named parameter in a single model. Points above the diagonal line indicate better DADVI or LRVB performance.

- SAA is hardly ever used for BBVI.¹ Why not?
 - Optimization literature predicts poor dimension dependence [Nemirovski et al., 2009]
 - Our experiments show that these results are too pessimistic
 - We prove better dimension dependence for SAA in some simple statistics models
 - A gap remains between theory and experiment.

¹Some exceptions I'm aware of: Giordano et al. [2018, 2022], Wycoff et al. [2022], Burrone et al. [2023].

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 - Our experiments show that these results are too pessimistic
 - We prove better dimension dependence for SAA in some simple statistics models
 - A gap remains between theory and experiment.
- Can I use SAA for very expressive approximating families?
 - We prove that the SAA fails for high-dimensional full-rank Gaussian approximations
 - We conjecture analogous problems with other expressive approximations

Given the benefits of DADVI over ADVI, **there's more work to be done!**

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Giordano, R.*, Ingram, M.*, Broderick, T. (* joint first authors), 2023.

(Arxiv preprint [here](#).)

- By fixing the randomness in the ADVI objective, DADVI provides BBVI that is easier to use, faster, and more accurate than stochastic gradient.
- The approximation used by DADVI will not work in high dimensions for sufficiently expressive approximating distributions (e.g., full-rank ADVI).
- There appears to be a gap between the optimization literature and BBVI practice in high dimensions for a class of practically interesting problems.

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Supplemental material

Linear response covariances and sampling uncertainty

Intractable objective:

$$\eta^* = \operatorname{argmin}_{\eta \in \mathbb{R}^{D_\eta}} \mathbb{E}_{\mathcal{N}_{\text{std}}(z)} [f(\eta, z)]$$

DADVI approximation:

$$\hat{\eta}(\mathcal{Z}_N) = \operatorname{argmin}_{\eta \in \mathbb{R}^{D_\eta}} \frac{1}{N} \sum_{n=1}^N f(\eta, z_n).$$

What is the error of the DADVI approximation $\hat{\eta} - \eta^*$?

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Answer: The same as a that of any M-estimator: asymptotically normal (as N grows)

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Posterior variances are often badly estimated by mean-field (MF) approximations.

Linear response (LR) covariances improve covariance estimates by computing *sensitivity* of the variational means to particular perturbations. [Giordano et al., 2018]

Example: With a correlated Gaussian $\mathcal{P}(\theta|y)$, the ADVI means are exactly correct, the ADVI variances are underestimated, and LR covariances are exactly correct.

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\Leftrightarrow What is the distribution of the DADVI error $\hat{\eta} - \eta^*$ under sampling of \mathcal{Z}_N ?

Answer: The same as a that of any M-estimator: asymptotically normal (as N grows)

Posterior variances are often badly estimated by mean-field (MF) approximations.

Linear response (LR) covariances improve covariance estimates by computing *sensitivity* of the variational means to particular perturbations. [Giordano et al., 2018]

Example: With a correlated Gaussian $\mathcal{P}(\theta|y)$, the ADVI means are exactly correct, the ADVI variances are underestimated, and LR covariances are exactly correct.

Both DADVI error and LR covariances can be computed from the DADVI objective.

Stochastic ADVI does not produce an actual optimum of any tractable objective, so LR and M-estimator computations are unavailable.

Posterior standard deviation accuracy

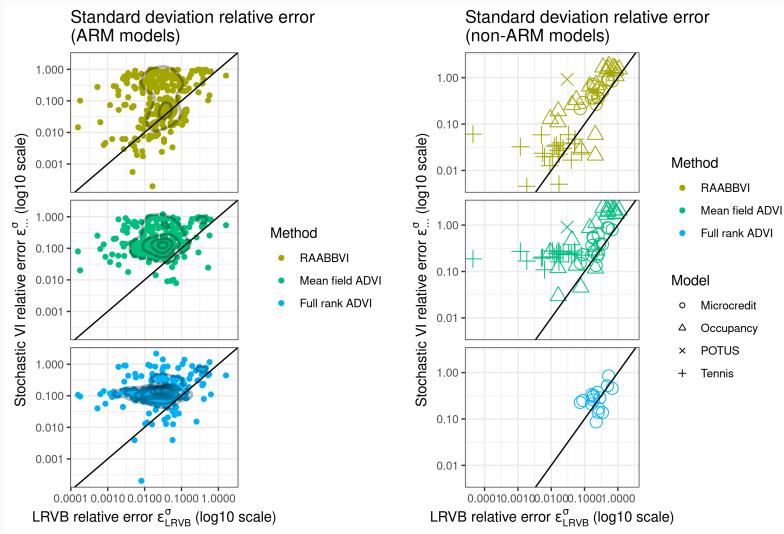


Figure 7: Posterior sd relative accuracy. Each point is a single named parameter in a single model. Points above the diagonal line indicate better DADVI or LRVB performance.

DADVI approximation error accuracy

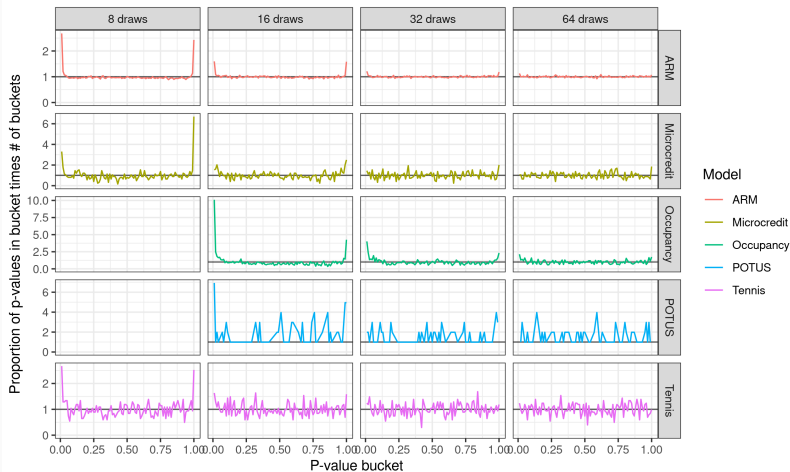


Figure 8: Density estimates of $\Phi(\varepsilon^\xi)$ for difference models. All the ARM models are grouped together for ease of visualization. Each panel shows a binned estimate of the density of $\Phi(\varepsilon^\xi)$ for a particular model and number of draws N . Values close to one (a uniform density) indicate good frequentist performance. CG failed for the Occupancy and POTUS models with only 8 draws, possibly indicating poor optimization performance with so few samples.

Intractable objective:

$$\eta^* = \operatorname{argmin}_{\eta \in \mathbb{R}^{D_\eta}} \mathbb{E}_{\mathcal{N}_{\text{std}}(z)} [f(\eta, z)]$$

SAA approximation (DADVI):

$$\hat{\eta}(\mathcal{Z}_N) = \operatorname{argmin}_{\eta \in \mathbb{R}^{D_\eta}} \frac{1}{N} \sum_{n=1}^N f(\eta, z_n).$$

The idea of optimizing \hat{F} instead of SG on F is old and well-studied in the optimization literature, where \hat{F} is known as the **Sample average approximation (SAA)**.

Yet SAA is rarely used for BBVI.² One possible reason is the following:

Theorem [Nemirovski et al., 2009]: In general, the error of both SG and SAA scale as $\sqrt{D_\theta/N}$, where, for SG, N is the *total number of samples used*.

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- For SAA, each z_n gets used once per optimization step (of which there are many).
- Often, in higher dimensions, SAA requires more optimization steps.

Corollary: [Kim et al., 2015] In general, for a given accuracy, the computation required for SAA scales worse than SG as the dimension D_θ grows.

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Previous theoretical results

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But we got good results with D_θ as high as 15,098 using only only $N = 30$. Why?

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Theorem [Giordano et al., 2023]: When $\mathcal{P}(\theta|y)$ is multivariate normal, and we use the mean-field Gaussian approximation, then, for any particular entry η_d of η , then $|\hat{\eta}_d - \eta_d^*| = O_p(N^{-1/2})$ irrespective of D_θ .

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Theorem [Giordano et al., 2023]: Assume $\mathcal{P}(\theta|y)$ has a “global-local” structure:

$$\theta = (\gamma, \lambda_1, \dots, \lambda_{D_\lambda}) \quad \mathcal{P}(\gamma, \lambda_1, \dots, \lambda_{D_\lambda} | y) = \prod_{d=1}^{D_\lambda} \mathcal{P}(\gamma, \lambda_d | y).$$

Assume that the dimension of γ and each λ_d stays fixed as D_λ grows.

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Proposal: The “in general” analysis of [Nemirovski et al., 2009] is too general for many practically interesting BBVI problems.

A negative result for expressive approximations

Theorem [Giordano et al., 2023]: Assume that $N < D_\theta$, and that we use a full-rank Gaussian approximation. Then the DADVI objective is unbounded below, and optimization of the DADVI objective will approach a degenerate point mass at $\operatorname{argmax}_\theta \log \mathcal{P}(\theta|y)$.

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Proof sketch: For any value of the variational mean, the DADVI objective only depends on $\mathcal{P}(\theta|y)$ evaluated in a subspace spanned by \mathcal{Z}_N . The variational objective can be driven to $-\infty$ by driving the variance to zero in the subspace orthogonal to \mathcal{Z}_N .

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Proposal: All sufficiently expressive variational approximations (e.g. normalizing flows) will fail in the same way in high dimensions. However, this pathology can be obscured and overlooked in practice by low-quality optimization.

Linear response covariances

Posterior variances are often badly estimated by mean-field (MF) approximations.

Example: With a correlated Gaussian $\mathcal{P}(\theta|y)$ with ADVI, the ADVI means are correct, but the ADVI variances are underestimated.

Take a variational approximation $\tilde{\eta} := \operatorname{argmin}_{\eta \in \mathbb{R}^{D_\eta}} \operatorname{KL}_{\text{VI}}(\eta)$. Often,

$$\mathbb{E}_{\mathcal{Q}(\theta|\tilde{\eta})}[\theta] \approx \mathbb{E}_{\mathcal{P}(\theta|y)}[\theta] \quad \text{but} \quad \operatorname{Var}_{\mathcal{Q}(\theta|\tilde{\eta})}(\theta) \neq \operatorname{Var}_{\mathcal{P}(\theta|y)}(\theta). \quad (1)$$

Example: Correlated Gaussian $\mathcal{P}(\theta|y)$ with ADVI.

Linear response covariances use the fact that, if $\mathcal{P}(\theta|y, t) \propto \mathcal{P}(\theta|y) \exp(t\theta)$, then

$$\left. \frac{d}{dt} \mathbb{E}_{\mathcal{P}(\theta|y, t)}[\theta] \right|_{t=0} = \operatorname{Cov}_{\mathcal{P}(\theta|y)}(\theta). \quad (2)$$

Let $\tilde{\eta}(t)$ be the variational approximation to $\mathcal{P}(\theta|y, t)$, and take

$$\operatorname{LRCov}_{\mathcal{Q}(\theta|\tilde{\eta})}(\theta) = \left. \frac{d}{dt} \mathbb{E}_{\mathcal{Q}(\theta|\tilde{\eta}(t))}[\theta] \right|_{t=0} = \left(\nabla_{\eta} \mathbb{E}_{\mathcal{Q}(\theta|\tilde{\eta})}[\theta] \right) \left(\nabla_{\eta}^2 \operatorname{KL}_{\text{VI}}(\tilde{\eta}) \right)^{-1} \left(\nabla_{\eta} \mathbb{E}_{\mathcal{Q}(\theta|\tilde{\eta})}[\theta] \right)$$

Example: For ADVI with a correlated Gaussian $\mathcal{P}(\theta|y)$, $\operatorname{LRCov}_{\mathcal{Q}(\theta|\tilde{\eta})}(\theta) = \operatorname{Cov}_{\mathcal{Q}(\theta|\tilde{\eta})}(\theta)$.